



Sizing truss structures using teaching-learning-based optimization



S.O. Degertekin*, M.S. Hayalioglu

Department of Civil Engineering, Dicle University, 21280 Diyarbakir, Turkey

ARTICLE INFO

Article history:

Received 14 February 2012

Accepted 7 December 2012

Available online 9 January 2013

Keywords:

Structural optimization

Truss structures

Teaching-learning-based optimization

ABSTRACT

Meta-heuristic search methods have been extensively used for optimization of truss structures over the past two decades. In this study, a new meta-heuristic search method called 'teaching-learning-based optimization' (TLBO) is applied for optimization of truss structures. The method makes use of the analogy between the learning process of learners and searching for designs to optimization problems. The TLBO consists of two phases: teacher phase and learner phase. 'Teacher phase' means learning from the teacher and 'learner phase' means learning by the interaction between learners. The validity of the method is demonstrated by the four design examples. Results obtained for the design examples revealed that although the TLBO developed slightly heavier designs than the other meta-heuristic methods in a few cases, it obtained results as good as or better than the other meta-heuristic optimization methods in terms of both the optimum solutions and the convergence capability in most cases.

© 2012 Elsevier Ltd. All rights reserved.

1. Introduction

Meta-heuristic search methods have been used extensively for optimization of truss structures over the past two decades. Ant colony optimization (ACO), harmony search (HS), particle swarm optimization (PSO), big bang–big crunch optimization (BB–BC) and artificial bee colony optimization (ABC) are the most popular meta-heuristic search methods. They also are classified as population-based or nature-inspired optimization methods. The main philosophy of all meta-heuristic optimization methods is to follow some heuristics in order to obtain the best solution for an optimization problem. Basically, meta-heuristic optimization algorithms generate new trial designs by following a random strategy which is "guided" however by inspiring criterion. Therefore, the optimization search is termed "meta-heuristic" to differentiate this class of algorithms from the fully heuristic optimization search [1]. Design optimization of skeletal structures using meta-heuristic search methods is an important field of engineering under continuous development. The state-of-art of the utilization of meta-heuristic algorithms in weight or cost optimization of skeletal structures has been recently reviewed by Lamberti [1] and Saka [2].

The ACO was originally proposed by Dorigo et al. [3] for optimization problems. The method simulates the foraging behavior of real-life ant colonies. The ACO attempts to model some of the fundamental capabilities observed in the behavior of ants as a method stochastic combinatorial optimization [4]. Ants can construct the shortest path from their colony to the feeding source and back through the use of pheromone trails [1]. In addition to its different

applications, the method has also been used for design optimization of structural systems. For example, truss structures were optimized by Camp and Bichon [5], Capriles et al. [6], Serra and Venini [7], and Hasancebi et al. [8]. Frame structures were optimized by Camp et al. [4], Kaveh and Shojaee [9], Hasancebi et al. [10], Kaveh and Talatahari [11].

HS was developed by Geem et al. [12] for solving combinatorial optimization problems. The method bases on the analogy between the musical process of searching for a perfect state of harmony and searching for solutions to optimization problems. The resemblance for example between jazz improvisation that seeks to find musically pleasing harmony and the optimization is that the optimum design process seeks to find the optimum solution as determined by the objective function [2]. After Lee and Geem [13] and Lee et al. [14] studies that utilized HS in optimization of truss structures, HS has been used for a variety of structural optimization problems including optimum design of geodesic domes [15], grillage systems [16], steel frames [17–21], and trusses [8,22,23]. In addition to standard implementation of HS algorithm, researchers developed many new features in HS. For example, Lamberti and Pappalettere [22] introduced an improved harmony search formulation where trial designs are generated including information on the gradients of cost function. The new HS formulation completed the optimization process in much less iterations than classical harmony search and other meta-heuristic optimization codes [22]. Hasancebi et al. [21] proposed an adaptive harmony search method for structural optimization. In the standard implementation of HS, appropriate constant internal values are assigned. Therefore, the efficiency of HS is directly related on chosen parameter value set. The adaptive harmony search algorithm proposed by Hasancebi et al. [21] incorporates a new approach for adjusting

* Tel.: +90 412 248 8402; fax: +90 412 248 8405.

E-mail address: sozgurd@gmail.com (S.O. Degertekin).

internal parameters automatically during the search for the most efficient optimization process [21].

The PSO method was developed by Kennedy and Eberhart [24]. It is based on the premise that social sharing of information among members of a species offers and evolutionary advantage [25]. The procedure involves a number of particles which represent the swarm being initialized randomly in the search space of an objective function. Each particle in the swarm represents a candidate solution of the optimum design problem. The particles fly through the search space and their positions are updated using the current position, a velocity vector and a time increment [2]. PSO has been used in optimization of skeletal structures [26–29]. Researchers introduced new features in the standard implementation of PSO. Li et al. [28,29] proposed a heuristic particle swarm optimizer (HPSO), which combines a PSO scheme and a HS scheme, for sizing optimization of truss structures. Kaveh and Talatahari [30,31] introduced a particle swarmer, ant colony optimization and harmony search scheme for truss structures with both discrete [30] and continuous variables [31]. The method combines a particle swarm optimizer with passive congregation (PSOPC), ant colony optimization (ACO) and harmony search scheme (HS).

The BB–BC proposed by Erol and Eksin [32] simulates the theories of the evolution of the universe. According to this theory, in the Big Bang phase energy dissipation produces disorder and randomness is the main feature of this phase; whereas, in the Big Crunch phase, randomly distributed particles are drawn into an order [33]. BB–BC algorithm was applied for sizing optimization of truss structures [34]. In order to improve convergence capability of standard BB–BC algorithm, Kaveh and Talatahari [33,35] developed hybrid BB–BC (HBB–BC) algorithm to optimize space trusses and ribbed domes. The HBB–BC method consists of two phases: a Big Bang phase where candidate solutions are randomly distributed over the search space, and a Big Crunch phase working as a convergence operator where the centre of mass is generated [33].

The ABC method was first developed by Karaboga [36] for numerical function optimization. The ABC is an optimization method based on the intelligent behavior of honey bee swarm. In the ABC method, each food source exploited by the bees represents a possible solution to given optimization problem. The location and amount of nectar from the flower patch correspond to the design variables and fitness function, respectively [37]. The ABC has successfully been applied to size optimization of truss structures with both continuous [37] and discrete variables [38]. Comparing the results from the ABC algorithm with other meta-heuristic methods demonstrated that ABC algorithm provides results as good as or better than other optimization algorithms for optimization of truss structures [37].

A novel optimization method called 'teaching-learning-based optimization (TLBO)' has been proposed by Rao et al. [39] for constrained mechanical design optimization problems. The method bases on the effect of influence of a teacher on learners and the effect of learners each other. Rao et al. [39] presented five different constrained benchmark test functions in order to demonstrate the robustness of TLBO. The results obtained from the design examples were compared with the other meta-heuristic optimization methods. The comparisons showed that the TLBO showed better performance with less computational effort over other meta-heuristic optimization methods. Rao et al. [40] developed the TLBO method for large scale non-linear optimization problems for finding global solutions. Five different benchmark problems are optimized using the TLBO method and the results are compared with the results of GA, ant colony system, bee algorithm and grenade explosion method. The results proved that the TLBO method is effective in terms of the computational effort, consistency and obtaining the near optimum solutions. After the pioneering studies of Rao et al. [39,40], the TLBO was employed for optimum design of

planar steel frames [41]. The efficiency of the method was verified by using three steel frames previously optimized by the GA, HS, and improved ACO. With regard to the number of analyses and the results for the frames presented in the study, the TLBO method demonstrated outstanding performance over the GA, ACO, HS, and improved ACO [41].

In this paper, the robustness of the TLBO will be investigated in the optimization of truss structures. Four popular benchmark truss structures existed in the current literature are presented to test the efficiency of the TLBO. The results obtained from the TLBO will be compared with those of other meta-heuristic optimization algorithms recently presented in literature like particle swarm optimization (PSO), heuristic particle swarm optimizer (HPSO), hybrid particle swarm optimization (HPSO), big-bang big-crunch optimization (BB–BC), heuristic particle swarm ant colony optimization (HPSACO), hybrid big bang big crunch optimization (HBB–BC), corrected multi-level and multi-point simulated annealing (CMLPSA), artificial bee colony optimization (ABC–AP), improved harmony search algorithm (IHS), efficient harmony search algorithm (EHS) and self-adaptive harmony search algorithm (SAHS).

The rest of this study is organized as follows. The formulation of optimum design problem is given in Section 2. The TLBO method is explained in Section 3. Optimization of truss structures using the TLBO is described in Sections 4. The results obtained from the TLBO are presented and compared with other meta-heuristic optimization methods in Section 5. Finally, conclusions are presented in Section 6.

2. The formulation of the optimum design problem

The minimum weight design problem for a truss structure can be formulated as:

$$\text{Find } X = [x_1, x_2, \dots, x_{ng}]$$

$$\text{to minimize } W(X) = \sum_{k=1}^{ng} x_k \sum_{i=1}^{mk} \rho_i L_i \quad (1)$$

subject to the following normalized constraints

$$g_{nl}^s(X) = \frac{|\sigma_{nl}|}{\sigma_{nu}} - 1 \leq 0, \quad 1 \leq n \leq nm, \quad 1 \leq l \leq nl \quad (2)$$

$$g_{nl}^b(X) = \frac{|\sigma_{cl}|}{\sigma_{cu}} - 1 \leq 0, \quad 1 \leq n \leq ncm, \quad 1 \leq l \leq nl \quad (3)$$

$$g_{jl}^d(X) = \frac{|d_{jl}|}{|d_{ju}|} - 1 \leq 0, \quad 1 \leq j \leq nn, \quad 1 \leq l \leq nl \quad (4)$$

$$x_{\min} \leq x_k \leq x_{\max} \quad k = 1, 2, \dots, ng \quad (5)$$

where X is the vector containing the design variables, $W(X)$ is the weight of the truss structure, ng is the total number of member groups (i.e. design variables), x_k is the cross-sectional area of the members belonging to group k , mk is the total number of members in group k , ρ_i is the density of member i , L_i is the length of member i , $g_{nl}^s(X)$, $g_{nl}^b(X)$ and $g_{jl}^d(X)$ are the constraint violations for member stress, member buckling stress and joint displacements of the structure. σ_{nl} and σ_{cl} are the member stress and the member buckling stress of the n th member due to loading condition l , σ_{nu} and σ_{cu} are their upper limits. d_{jl} is the nodal displacement of the j th translational degree of freedom due to loading condition l , d_{ju} is its upper limit. nl is the number of load conditions, nm is the number of nodes, max and min are the upper and lower limits for cross-sectional area.

The optimum design of truss structures must satisfy optimization constraints stated by Eqs. (2)–(5). In this study, the constraints are handled by using a modified feasible-based mechanism [30].

Download English Version:

<https://daneshyari.com/en/article/510634>

Download Persian Version:

<https://daneshyari.com/article/510634>

[Daneshyari.com](https://daneshyari.com)